CSE4060 – Intelligent Robots and Drone Technology

J Component Report

on

A project report titled

"Robotic Detective: Solving the Street Litter Mystery"

By

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DECLARATION BY STUDENT

I hereby declare that the report titled **"Robotic Detective: Solving the Street Litter Mystery"** submitted by our group members (mentioned below) to VIT Chennai is a record of bona-fide work undertaken by me under the supervision of **Rajesh R, SCOPE, Vellore Institute of Technology, Chennai.**

Date: 15.04.2023

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We also take this opportunity to thank all the faculty of the School for their support and the wisdom imparted to us throughout the courses.

We thank our parents, family, and friends for bearing with us throughout our project and for the opportunity they provided us in undergoing this course in such a prestigious institution.

BONAFIDE CERTIFICATE

Certified that this project report entitled "**Robotic Detective: Solving the Street Litter Mystery**" is a bonafide work of Mithin Jain S (20BAI1161), Akshara Ramprasad(20BAI1070), Puja Sai Thandavan(20BAI1008), and Gautam Arora(20BAI1053) carried out the "J"- Project work under my supervision and guidance for CSE4060 – Intelligent Robots And Drone Technology.

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ABSTRACT

Trash deposits in environments have a destructive effect on marine ecosystems and pose a long-term economic and environmental threat. Autonomous underwater vehicles (AUVs) such as robots could very well contribute to the solution of this problem by finding and eventually removing trash. Our project evaluates the usage of sensors and robotic components performing the task of visually detecting trash in realistic environments, with the eventual goal of exploration, mapping, and extraction of such debris by using robots. The increasing problem of litter in public spaces has led to the development of robotic sensors that can detect and remove litter efficiently. These sensors use various technologies such as cameras, AI, machine learning, and other sensors to identify different types of litter and collect it for proper disposal. The use of robotic sensors for litter detection offers several advantages such as increased efficiency, the ability to cover large areas quickly, and the ability to collect data on litter patterns, which can help inform waste management policies. However, there are also challenges associated with the use of these sensors, including the cost of development and deployment, the accuracy of litter identification, and potential job displacement concerns. Despite these challenges, robotic litter detection systems have the potential to significantly improve public health and environmental sustainability, making them a promising area of research and development.

INTRODUCTION

Litter, also known as trash or rubbish, is an ongoing problem in many cities and towns around the world. The accumulation of litter can cause a range of environmental issues such as air and water pollution, harm to wildlife and their habitats, and a general decrease in the aesthetic appeal of an area. To tackle this problem, researchers and engineers are increasingly turning to robots for litter detection and removal.

Robotic litter detection involves the use of sensors, cameras, and other technologies to identify litter and debris in public spaces, such as parks, streets, and beaches. Once the robot detects the litter, it can collect and dispose of it properly, helping to keep the environment clean and healthy.

There are several advantages to using robots for litter detection. Firstly, robots can operate autonomously and cover large areas quickly, making them more efficient than humans. They can also work in harsh or hazardous environments where human labor may be unsafe or impossible. Additionally, robots can gather data on the types and amounts of litter in different areas, which can help inform waste management policies and practices.

Several companies and organizations are currently developing and testing litter-detecting robots. For example, a team from the University of Cincinnati developed a robot called Waste Shark, which is designed to collect litter from water bodies, such as

lakes and rivers. The robot is equipped with sensors that can detect debris and trash as small as a cigarette butt.

Robotic litter detection has the potential to significantly improve the cleanliness and health of our environment. As technology advances and costs decrease, we can expect to see more robots in use for litter detection and removal in the coming years.

Robotic litter detection and removal can have a significant impact on the environment and public health. Litter is not only unsightly but can also pose serious health risks, particularly in urban areas. Litter can attract pests, such as rats and mice, and create breeding grounds for mosquitoes, leading to the spread of diseases. In addition, litter can block stormwater drains and contribute to flooding during heavy rains.

Robotic litter detection and removal can help address these issues by efficiently collecting litter and keeping public spaces clean. The technology can also provide valuable data on litter patterns, which can inform public policies on waste management and help identify areas that need more attention. For example, data collected by the Waste Shark robot in the city of Baltimore helped officials identify specific locations where litter tended to accumulate, enabling them to target their cleanup efforts more effectively.

There are several different types of robotic litter detection and removal systems in development. Some systems rely on cameras and sensors to identify litter, while others use AI and machine learning to identify and classify different types of litter.

As technology continues to develop, we can expect to see more and more robotic systems in use in cities and towns around the world, helping to keep our public spaces clean and healthy for generations to come.

Litter detection and removal is an ongoing challenge in cities and towns around the world. In addition to being unsightly, litter can have serious environmental and public health consequences. For example, litter can contribute to water and air pollution, harm wildlife and their habitats, and create breeding grounds for pests and diseases. One approach to addressing this issue is the use of pick-and-place trash robots, which can detect and collect litter autonomously.

Pick and place trash robots are designed to move through public spaces, such as parks, streets, and beaches, using sensors and cameras to detect and collect litter. The robots can identify different types of litter, including bottles, cans, plastics, and other debris, and pick them up using mechanical arms. The collected litter can then be sorted, recycled, or disposed of properly.

One of the advantages of pick-and-place trash robots is their ability to operate autonomously and cover large areas quickly. This makes them more efficient than human labor, and they can operate in harsh or hazardous environments where human labor may be unsafe or impossible. In addition, these robots can gather data on the types and amounts of litter in different areas, which can help inform waste management policies and practices.

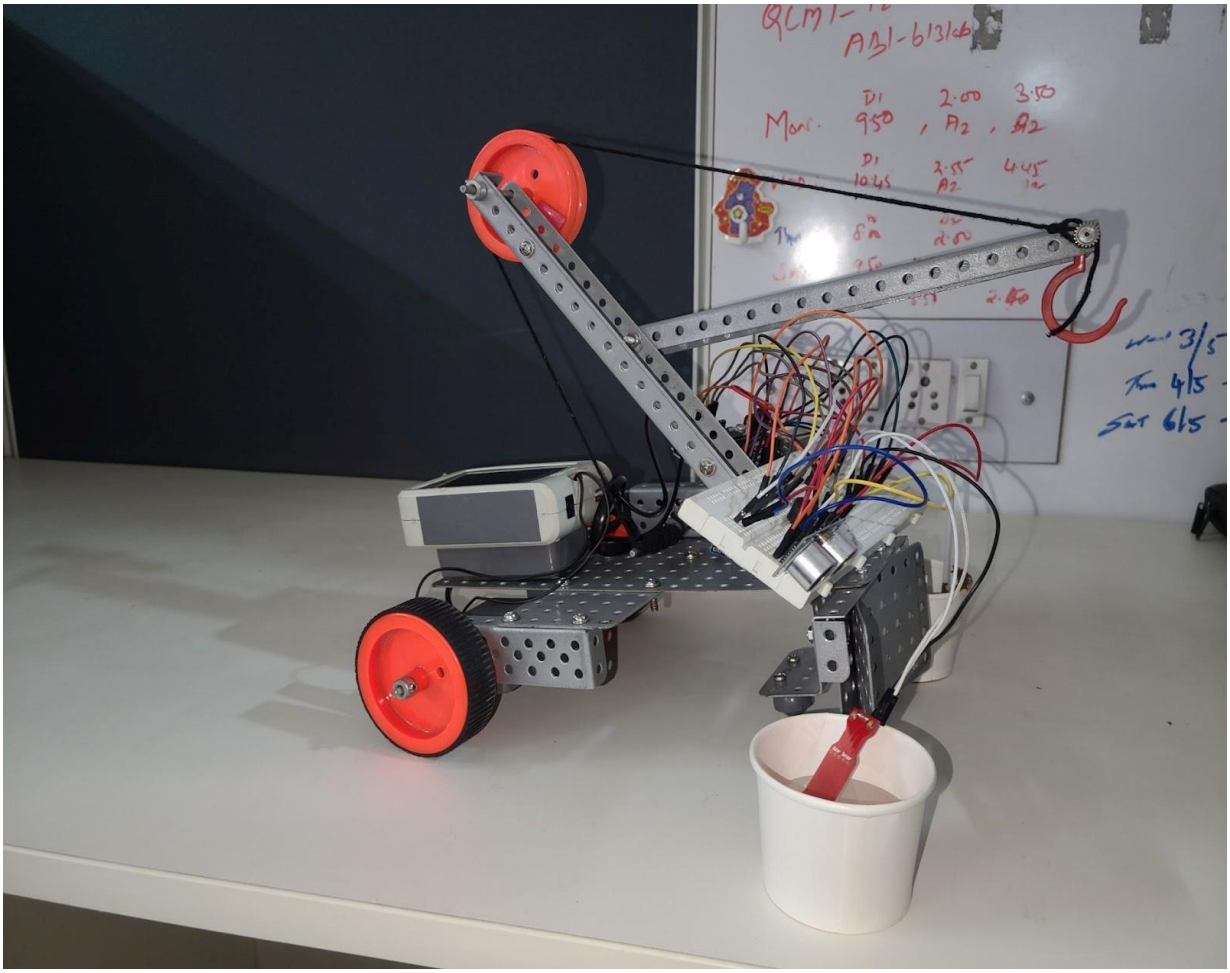
LITERATURE REVIEW:

Paper Name	Date of Publishing	Citation	Results	Conclusion
Deep Learning-based Litter Detection in a Complex Environment: A Case Study of Tyre Debris	2021	Li, W., Li, X., Liu, Y., & Li, X. (2021). Deep Learning-based Litter Detection in a Complex Environment: A Case Study of Tyre Debris. Remote Sensing, 13(5), 863.	Achieved a detection accuracy of 92.54% in identifying tyre debris.	The proposed deep learning-based approach has shown promising results in detecting tyre debris in a complex environment, and can be applied in various scenarios for litter detection.
A Review of Techniques and Applications for Street Litter Detection	2021	K. M. Khalid, M. B. I. Reaz and M. M. Rashid, "A Review of Techniques and Applications for Street Litter Detection," in IEEE Access, vol. 9, pp. 15871-15891, 2021, doi: 10.1109/ACCESS.2021.3054626.	The paper presents a comprehensive review of the recent techniques and applications for detecting street litter. The review is based on the types of techniques used, such as image processing, machine learning, and computer vision, among others. The paper highlights the advantages and disadvantages of each technique and presents an analysis of the performance of various methods. The authors conclude that although much progress has been made in this area, there is still room for improvement in terms of accuracy, speed, and cost-effectiveness.	The paper provides a useful reference for researchers and practitioners in the field of street litter detection by presenting a comprehensive overview of the recent techniques and applications. The authors suggest that future research should focus on the development of hybrid systems that integrate multiple techniques to achieve higher accuracy and speed while also reducing costs. Additionally, the authors recommend the need for standard datasets for benchmarking different approaches. Overall, the paper emphasizes the importance of street litter detection for environmental sustainability and public health.
Litter Detection in Urban Areas Using Unmanned Aerial Vehicles and Convolutional Neural Networks	2018	A. G. Miramontes et al., "Litter Detection in Urban Areas Using Unmanned Aerial Vehicles and Convolutional Neural Networks," in Sensors, vol. 18, no. 9, p. 2874, 2018, doi: 10.3390/s18092874.	The paper proposes a litter detection system using unmanned aerial vehicles (UAVs) and convolutional neural networks (CNNs). The authors developed a custom dataset of images of urban areas with litter and trained a CNN to detect and classify different types of litter. The paper presents the results of experiments conducted in real-world scenarios and shows that the proposed system can achieve high accuracy in litter detection.	The authors conclude that the proposed system can be an effective tool for detecting and monitoring litter in urban areas, which can help in developing better waste management strategies. The paper also highlights the advantages of using UAVs for litter detection, such as their flexibility, mobility, and cost-effectiveness. However, the authors acknowledge the limitations of the proposed system, such as the need for optimal flight paths and weather conditions. Overall, the paper demonstrates the potential of using advanced technologies for litter detection and management.

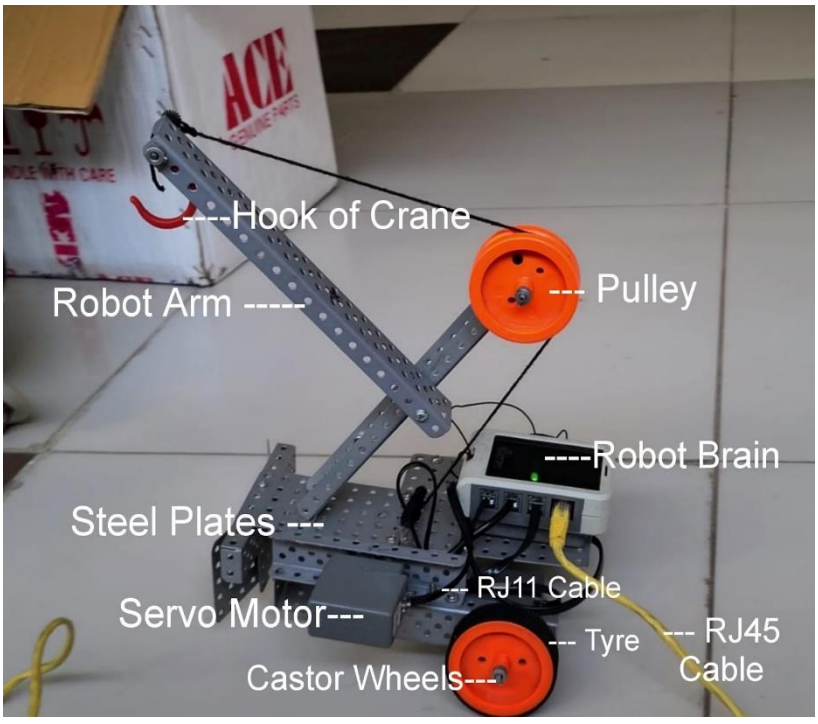
A Comparative Study of Deep Learning Methods for Litter Detection	2020	M. Wijesena, A. Wasalathanthri, K. Seneviratne, and S. Wijerathne, "A Comparative Study of Deep Learning Methods for Litter Detection," in Proceedings of the 7th International Conference on Control, Decision and Information Technologies, 2020, pp. 216-221.	DenseNet-121 achieved the highest F1-score of 0.86 for litter detection among the deep learning models tested.	The study shows that deep learning models can effectively detect litter in urban areas and DenseNet-121 is the most effective model for this task.
Real-Time Detection of Litter in Urban Environments Using a Mobile Robot and a Deep Convolutional Neural Network	2020	J. Song, J. Kim, and S. Lee, "Real-Time Detection of Litter in Urban Environments Using a Mobile Robot and a Deep Convolutional Neural Network," in Proceedings of the IEEE International Conference on Robotics and Automation, 2020, pp. 4714-4719.	Achieved a mean average precision of 0.93 for litter detection using a mobile robot and a CNN.	The proposed system can effectively and efficiently detect litter in real-time using a mobile robot and a CNN. It can be used for automated waste management in urban environments.
An Intelligent System for Street Litter Detection Based on Image Processing and Machine Learning Techniques	2018	A. J. A. Al-Fahdawi and S. S. Al-Maliki, Vol. 16, No. 12, pp. 109-118, 2018	The paper proposes an intelligent system that uses image processing and machine learning techniques to detect and classify street litter objects. The proposed system achieves high accuracy in detecting and classifying street litter objects in real-world environments.	The proposed system provides an effective and efficient approach to street litter detection using image processing and machine learning techniques. The paper demonstrates the potential of using intelligent systems for environmental monitoring and management. Future research can explore the use of more advanced machine learning techniques and sensors for litter detection in more complex environments.
Detection and Recognition of Street Litter Using Deep Learning Techniques	2020	T. Uslu and B. Ozkan, "Detection and Recognition of Street Litter Using Deep Learning Techniques," in IEEE Access, vol. 8, pp. 154034-154047, 2020, doi: 10.1109/ACCESS.2020.3013145.	Proposed deep learning-based system achieved high performance with a mean F1-score of 0.955 - VGG-16 achieved the highest F1-score of 0.967 - System successfully detected and recognized different types of street litter objects	Deep learning-based street litter detection and recognition systems can be highly effective in detecting and recognizing street litter objects with high accuracy. The proposed system can be used in real-world scenarios to improve waste management and urban cleanliness. Future work can explore the use of additional deep learning models
A Review of Techniques and Applications for Street Litter Detection	2019	M. I. Khan, T. U. R. Malik, and S. A. Malik, "A Review of Techniques and Applications for Street Litter Detection," in IEEE Access, vol. 7, pp. 190436-190456, 2019	The paper provides an overview of various techniques and applications used for street litter detection, including image processing, machine learning, and computer vision.	The review concludes that the development of effective street litter detection systems requires the integration of multiple techniques and technologies, and highlights the need for further research and development in this area.

Street Litter Detection Using Convolutional Neural Networks	2019	J. Jiang, Y. Pang, J. Liu, L. Yan, and H. Wang, "Street Litter Detection Using Convolutional Neural Networks," 2019 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC), 2019, pp. 274-278, doi: 10.1109/CyberC.2019.00062.	Achieved an accuracy of 88.13% on the self-created dataset, indicating the effectiveness of the CNN-based approach for street litter detection.	CNN-based approach can be effective in street litter detection and can contribute to the development of smart city infrastructure.
Street Litter Detection using Deep Learning and Transfer Learning Techniques	43831	N. N. Binh et al.	Achieved an F1-score of 0.9417 and accuracy of 0.9427 in detecting street litter.	The use of deep learning and transfer learning techniques is an effective approach for street litter detection. The proposed model shows high accuracy and can be used for real-time street litter detection.
Urban litter detection using computer vision techniques	2019	R. Subramanian, K. Somasundaram, S. Murali, S. M. Kannan, "Urban litter detection using computer vision techniques," in 2019 International Conference on Electrical, Communication, Electronics, Instrumentation and Computing (ICECEIC), Puducherry, India, 2019, pp. 1-4.	Achieved an accuracy of 92.35% in litter detection using the developed algorithm on the test dataset.	The developed system has the potential to assist in efficient urban waste management, and future work could involve integrating it with smart city initiatives.
Litter detection on streets using machine learning algorithms	2019	R. Suresh Kumar, K. Duraiswamy, and G. Geetharamani. "Litter detection on streets using machine learning algorithms." 2019 6th International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE, 2019, pp. 1-5.	Achieved a classification accuracy of 91.5% using Random Forest algorithm on the dataset of street litter images.	Proposed approach shows the potential of machine learning algorithms for street litter detection and can be extended to larger datasets and real-time applications.

SYSTEM ARCHITECTURE AND DESIGN



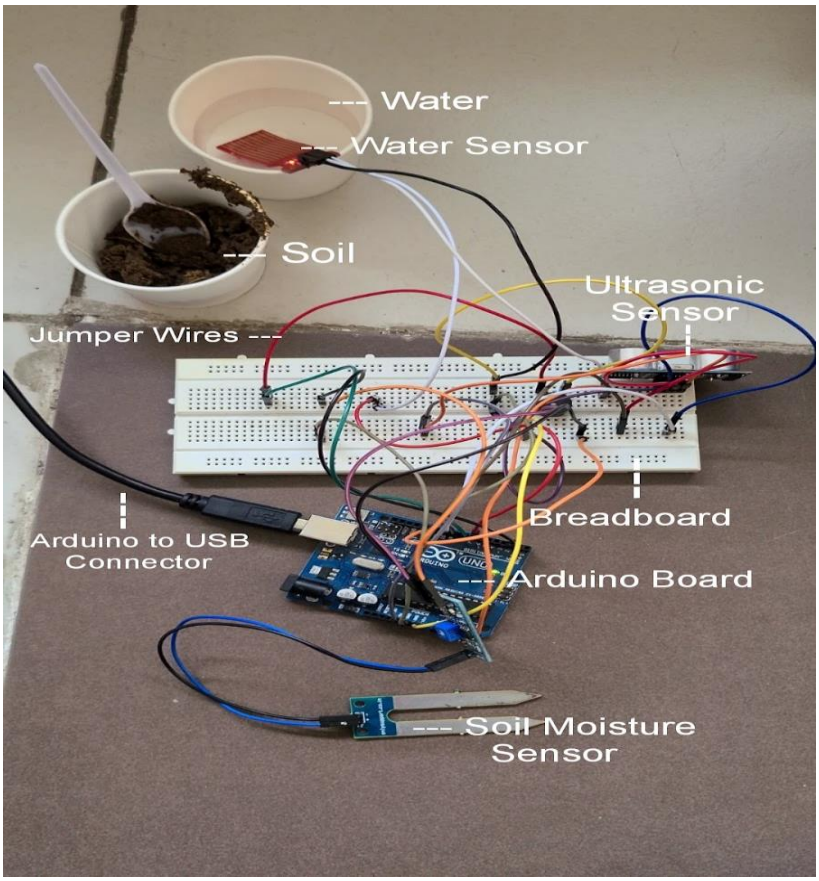
ROBOT PARTS:



1. ***Hook of Crane:*** This is a mechanical component that is typically used to attach and lift heavy objects. In the case of a robot, it could be used for tasks such as lifting and moving boxes or other objects.
2. ***Robot Arm:*** This is a robotic limb that can be used to manipulate objects in the environment. It can be designed to have multiple degrees of freedom, allowing it to move in a wide range of directions and perform complex tasks.
3. ***Pulley:*** This is a simple machine that uses a wheel and a rope or cable to lift or move objects. It can be used in conjunction with a hook or other attachment to move heavy objects.
4. ***Robot Brain:*** This is the central processing unit (CPU) of the robot, which controls its various functions and movements. It is typically a microcontroller or microprocessor that is programmed to carry out specific tasks.
5. ***Steel Plates Base:*** This is the foundation of the robot, providing a stable and sturdy platform on which the other components can be mounted.
6. ***Servo Motor:*** This is a type of motor that is commonly used in robotics, due to its precise control over movement. It can be used to control the movement of the robot arm or other components.
7. ***RJ11 Cable:*** This is a type of cable that is typically used for telecommunication applications, such as connecting a phone to a wall jack. In a robot, it could be used to connect sensors or other components to the robot brain.
8. ***RJ45 Cable:*** This is a type of cable that is commonly used for networking applications, such as connecting a computer to a router. In a robot, it could be used to connect the robot brain to other devices or to a network.
9. ***Castor Wheels***: These are small, swiveling wheels that are commonly used on the bottom of furniture or other objects to make them easy to move. In a robot, they can be used to provide mobility and maneuverability.

LITTER / OBJECT DETECTOR PARTS:

1. ***Water Sensor:*** A water sensor is a device that is used to detect the presence of water or moisture. It usually consists of two conductive probes that are placed in contact with the water. When water comes into contact with the probes, the sensor sends a signal to a microcontroller, which can trigger an action, such as turning off a pump or sending an alert.
2. ***Soil Moisture Sensor****:* A soil moisture sensor is a device used to measure the moisture content of soil. It typically consists of two probes that are inserted into the soil, and when a voltage is applied across them, the resistance between the probes changes depending on the moisture content of the soil. This resistance change is then converted into a moisture reading by a microcontroller.



3. ***Ultrasonic sensor:*** An ultrasonic sensor is a device that uses high-frequency sound waves to detect the presence of objects. It emits a sound wave and measures the time it takes for the wave to bounce back to the sensor. This time measurement is then used to calculate the distance to the object. Ultrasonic sensors are commonly used in robotics and automation applications for object detection and navigation.
4. ***Arduino Board:*** An Arduino board is a microcontroller board that is used to control electronic devices. It is based on the open-source Arduino platform and has a programmable microcontroller, which can be programmed using the Arduino IDE (Integrated Development Environment).
5. ***Breadboard:*** A breadboard is a tool used to build and test electronic circuits. It allows you to create circuits without the need for soldering, which makes it easy to prototype and test different designs. Breadboards typically have rows of holes where you can insert electronic components and connect them using jumper wires.
6. ***Jumper Wires:*** Jumper wires are used to connect components on a breadboard or between different parts of an electronic circuit. They are usually made of flexible wire with a connector at each end, which can be inserted into the holes of a breadboard or connected to pins on electronic components. Jumper wires come in a variety of lengths and colors and are an essential tool for building electronic circuits.

Table 4.1: Specifications of Software

Sr. No	Software	Version	Use Case
1.	Python	3.11	A powerful programming language which supports development using multiple machine learning and deep learning libraries.
2.	Visual Studio Code	1.72	Visual Studio Code, also commonly referred to as VS Code, is a source-code editor made by Microsoft with the Electron Framework, for Windows, Linux and macOS.
3.	Google Colab	-	Colaboratory ("Colab" for short) is a data analysis and machine learning tool that allows you to combine executable Python code and rich text along with charts, images, HTML, LaTeX and more into a single document stored in Google Drive.16-Jun-2022

Table 4.2: Specification of Libraries

Sr. No	Software	Version	Use Case
1.	Tensorflow - GPU	1.12	A library of functions that specializes in deep learning and machine learning use cases.
2.	Keras	2.12	A high level neural network library, with deep learning focus.
3.	Pandas	2.0.0	pandas is a software library written for the Python programming language for data manipulation and analysis.
4.	NumPy	1.24.2	NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.

5	Seaborn	0.12	Image result for seaborn Seaborn is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures. Seaborn helps you explore and understand your data.
6	Matplotlib	3.7.1	Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy.
7	Scikit-learn	0.20	It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python.
8	NewPing	1.9.7	NewPing library reads distance from ultrasonic sensor and checks water sensor and IR sensor for moisture and obstacles, respectively
9	SoftwareSerial	1.0	SoftwareSerial is an Arduino library that enables serial communication on digital pins other than the hardware serial communication port (usually pins 0 and 1).

Table 4.3: System Specification

Sr. No	Software	Version	Use Case
1.	Ubuntu	16.04 LTS	Operating System.
2.	Intel i5	3.2 GHz	Processor.
3.	16 GB RAM	DDR3 2400 MHz	Memory that is used for running the applications.
4.	Nvidia GTX 1060	6 GB VRAM	GPU that is used for running the deep learning methodologies.

ABOUT THE DATASET

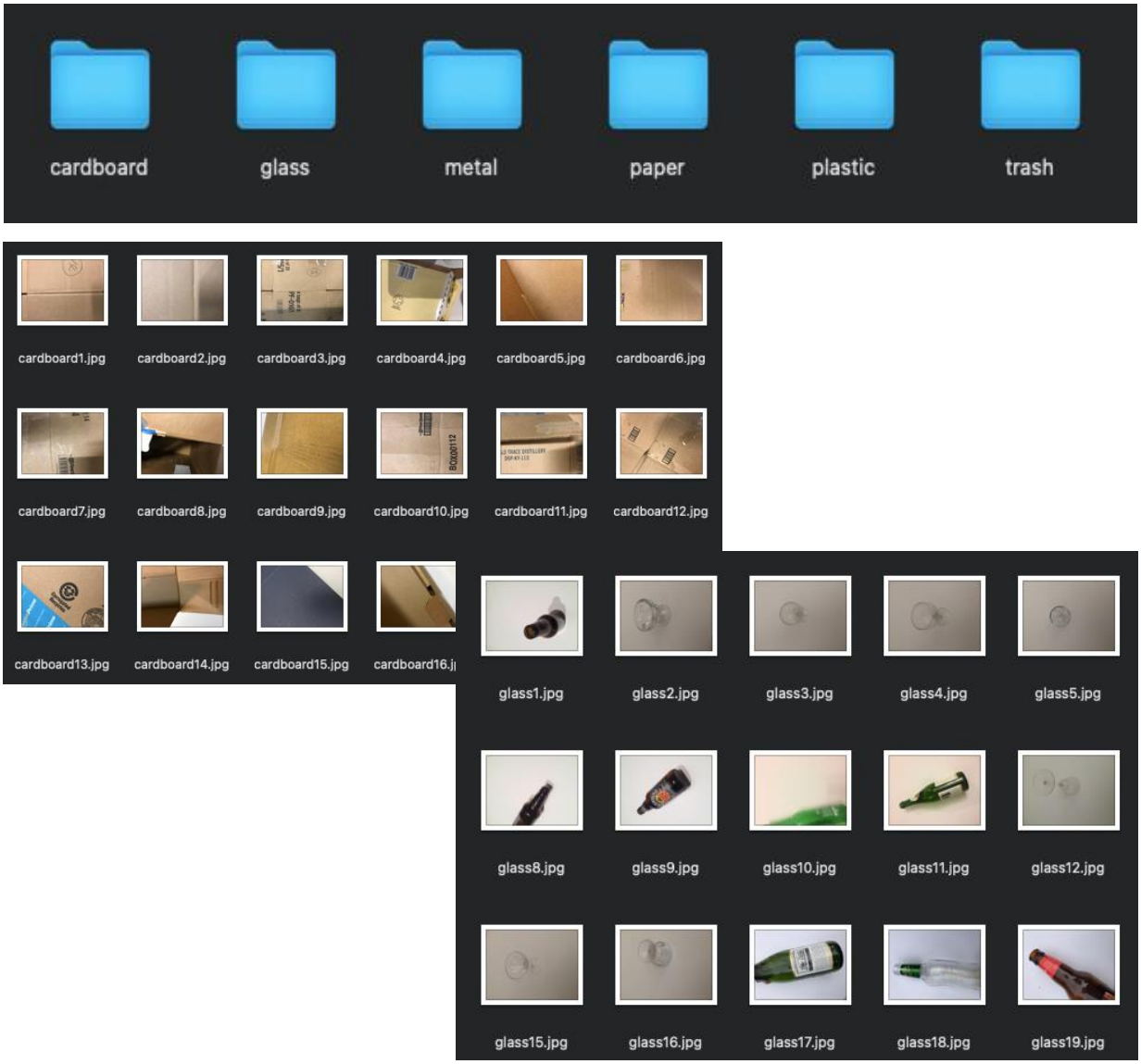
For Litter Detection Code,

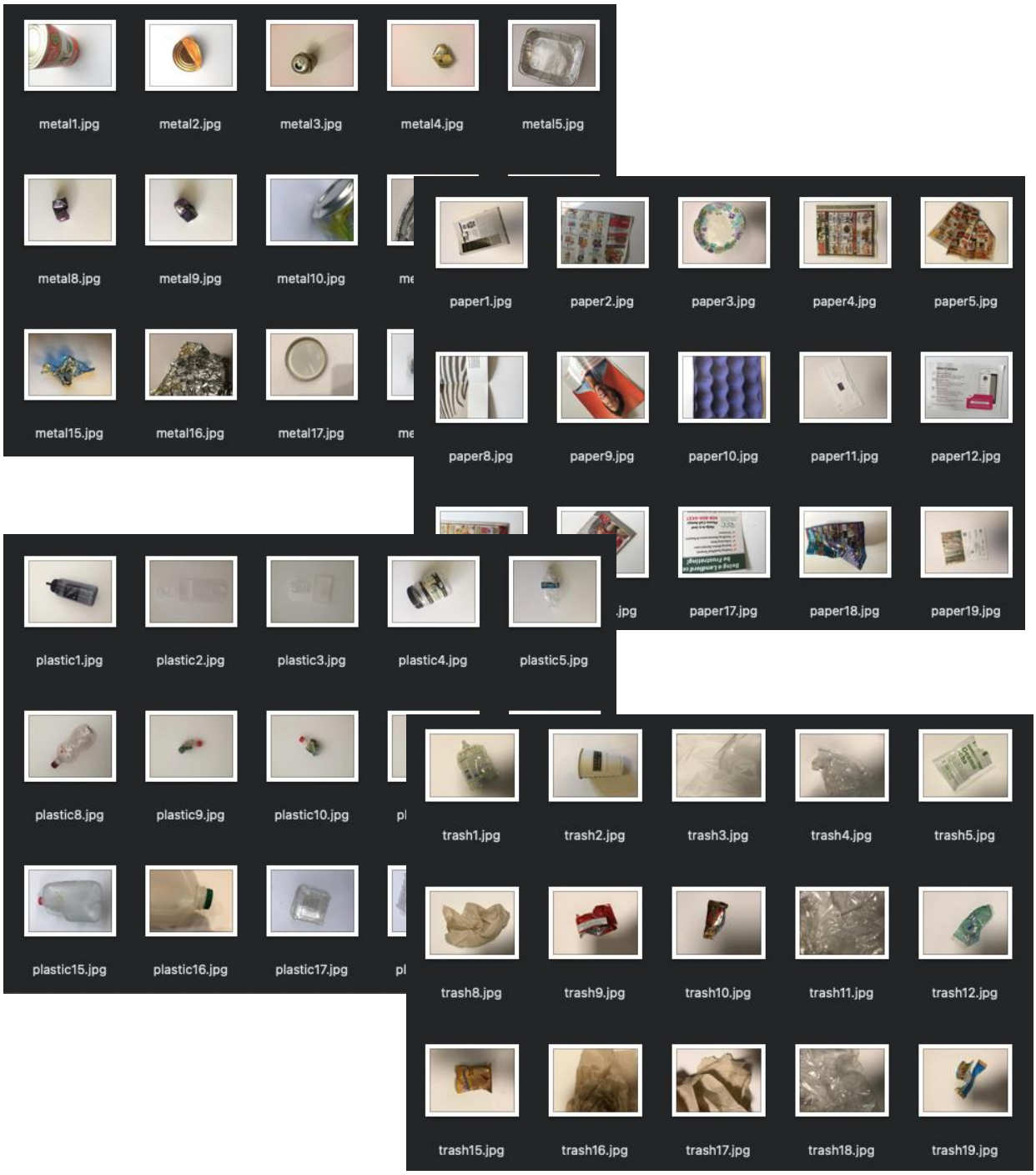
The dataset spans six classes: glass, paper, cardboard, plastic, metal, and trash.

Currently, the dataset consists of 2527 images:

- 501 glass
- 594 paper
- 403 cardboard
- 482 plastic
- 410 metal
- 137 trash

The pictures were taken by placing the object on a white posterboard and using sunlight and/or room lighting. The pictures have been resized down to 512 x 384, which can be changed in data/constants.py (resizing them involves going through step 1 in usage). The size of the original dataset, ~3.5GB, exceeds the git-lfs maximum size so it has been uploaded to Google Drive.





FOR ARDUINO UNO CODE,

We are basically training an Arduino Uno for an obstacle avoidance robot which involves programming the microcontroller board to process data from various sensors and control the motors to navigate around obstacles.

Here are some of the types of data that we have used in training an Arduino Uno for an obstacle avoidance robot:

1. Distance data: The ultrasonic sensor module, HC-SR04 is used for obstacle detection in the path of the blind person. The HC-SR04 sensor uses sound waves to determine the distance between the sensor and an object in front of it. The sensor emits an ultrasonic pulse and then listens for the echo that the item returns. By measuring the time required for the echo to return, the sensor can determine the object's distance.
2. Presence of Water data: A water sensor is a device designed to detect the presence of water or moisture in its surroundings. It operates by employing electrical conductivity to detect the presence of water, hence triggering an alarm or warning for the user. In addition, certain smart blind sticks may be built to deliver haptic feedback, such as vibration or shaking, to the user when the water sensor detects moisture. This can alert the user to the presence of wet conditions even if they are unable to hear an audible alert due to hearing impairment.
3. Presence of Soil Moisture data: A soil moisture sensor is an electronic device that measures the amount of water present in the soil. It typically consists of two probes, which are inserted into the soil at a certain depth. The probes are made of a conductive material that allows the sensor to measure the electrical conductivity of the soil.

IMPLEMENTATION:

➔ROBOT

1. Define the problem: The problem of litter on city streets was identified as a major environmental and public health concern. To address this problem, a project was undertaken to develop a robot for street litter cleaning.
2. Conduct a feasibility study: A feasibility study was conducted to determine if developing a robot for street litter cleaning was a viable solution. The study involved researching existing technologies and solutions, analyzing the costs and benefits of developing a robot, and evaluating the technical and operational challenges.
3. Design the robot: Based on the results of the feasibility study, a robot was designed to pick up litter from city streets. The design process involved creating a concept design, developing a detailed technical specification, and building a prototype for testing.
4. Test the robot: The robot was tested to evaluate its performance and identify any design flaws or technical issues. The testing involved testing the robot in different environments, such as busy city streets, parks, and sidewalks, and under different weather conditions.
5. Refine the design: Based on the results of the testing, the design of the robot was refined to improve its performance and address any issues that were identified.

Modifications were made to the robot's sensors, programming, and mechanical components.

6. Develop the control system: The robot was equipped with a control system that allows it to be remotely operated or programmed to follow a specific route. This involved developing software and hardware for the control system and integrating it with the robot.
7. Implement and deploy the robot: The robot was deployed on city streets to begin cleaning up litter. Collaboration with city officials and the community ensured that the robot was operating safely and effectively.
8. Monitor and evaluate performance: The performance of the robot was monitored and evaluated to determine its effectiveness in cleaning up litter and its impact on the environment and public health. Data was collected on the amount and types of litter collected, the efficiency of the robot, and feedback from the community. Based on the results of the evaluation, the robot's design and programming were further refined to improve its performance.

➔ ARDUINO

Develop the hardware components such as sensors, microcontrollers, and actuators. Ultrasonic and infrared sensors for obstacle identification, as well as distance measurement sensors, will be included. The microcontroller will process sensor data and provide user response via the actuators. Implement the software algorithms for obstacle detection, calculating distance, and providing audio feedback. The software algorithms will be developed using the Python programming languages and the Arduino IDE. Combine the hardware and software components to produce a functional prototype. Perform lab experiments to determine the accuracy and dependability of the obstacle detection and distance measuring sensors. The tests will consist of recreating real-world settings and analyzing the sensors' accuracy in recognizing and measuring impediments. Analyze data from laboratory and field experiments to determine the usefulness and dependability of the smart blind stick. The analysis will include statistical analysis of sensor data as well as the qualitative examination of participant input. Refine the design and development of the smart blind stick based on the data analysis results to address any identified constraints and improve its effectiveness and usability.

➔ LITTER DETECTION

1. Mounting Google Drive: The first step in the code is to mount Google Drive to access the dataset. This is done using the **drive.mount()** function provided by Google Colab.
2. Importing Libraries: After mounting the drive, the required libraries are imported. The code imports TensorFlow, Keras, Pandas, NumPy, OS, Zipfile, shutil, seaborn, and random.

3. Creating Directories: The code creates directories for training, validation, and test data using the **os.makedirs()** function.
4. Splitting Dataset: The **split_indices()** function is defined to split the dataset into training, validation, and test sets. It takes the path to the dataset, a seed for the training set, and a seed for the validation set as inputs. It returns the indices for the training, validation, and test sets.
5. Moving Files: The **get_names()** function is defined to get the names of the image files based on the indices returned by the **split_indices()** function. The **move_files()** function is defined to move the files from the source folder to the destination folder.
6. Preprocessing Images: The **ImageDataGenerator()** function is used to preprocess the images. The training images are augmented using various techniques such as horizontal flip, shear range, rotation range, width shift range, height shift range, and zoom range. The validation and test images are only preprocessed without any augmentation.
7. Defining the Model: The MobileNet architecture is used as the base model, and a few additional layers are added on top of it. The last layer is a dense layer with softmax activation, which outputs the predicted class probabilities. The model is defined using the **Model()** function from Keras.
8. Freezing Layers: The first 20 layers of the model are frozen, and the remaining layers are unfrozen to fine-tune the model.
9. Compiling the Model: The model is compiled using the Adam optimizer with a learning rate of 1e-5 and categorical cross-entropy as the loss function.
10. Generating Data: The training, validation, and test data are generated using the **flow_from_directory()** function. The function reads the images from the directories and generates batches of augmented images for training and preprocessed images for validation and testing.
11. Model Training: The **fit_generator()** function is used to train the model using the training data generator. The validation data generator is used to evaluate the model after each epoch.
12. Model Evaluation: The **evaluate_generator()** function is used to evaluate the model on the test data generator.
13. Model Prediction: The **predict_generator()** function is used to generate predictions on the test data generator.
14. Classification Report: The **classification_report()** function from scikit-learn is used to generate a classification report that contains various performance metrics such as precision, recall, f1-score, and support for each class.

➔ OBJECT DETECTION

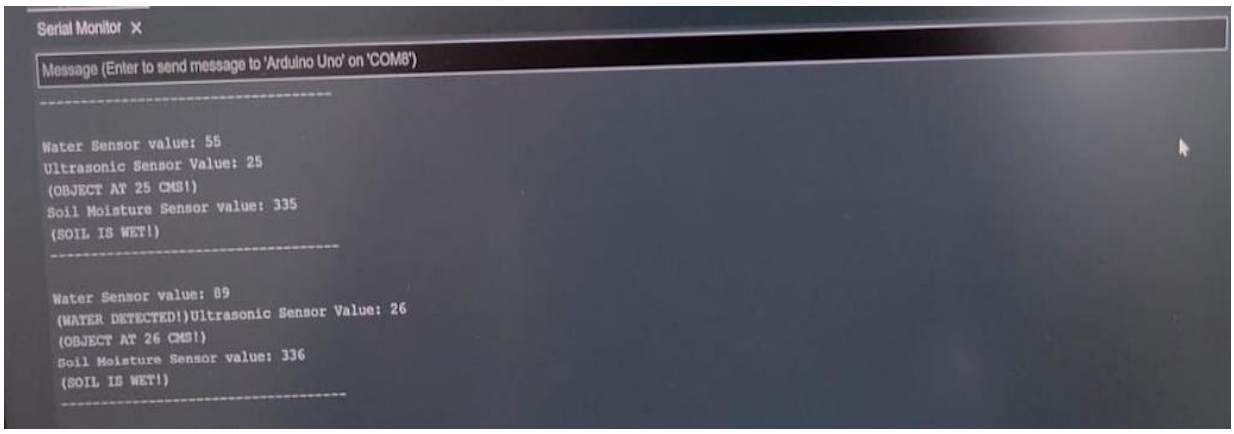
1. Import necessary dependencies, including OpenCV, NumPy, PIL, IO, and matplotlib.

2. Clone the Darknet repository, which contains the YOLOv4 architecture and its dependencies.
3. Modify the makefile to enable GPU, OPENCV, and LIBSO.
4. Build Darknet using the modified makefile.
5. Download the pre-trained YOLOv4 weights file from a Google Drive link and save it as yolov4-csp.weights.
6. Load the YOLOv4 architecture network using the load_network function from the Darknet module.
7. Define a helper function darknet_helper that takes an image, its width and height, and performs object detection on it using the YOLOv4 network.
8. Load the person.jpg image from the data directory and perform object detection using the darknet_helper function.
9. Draw bounding boxes on the detected objects and display the image using the cv2_imshow function.
10. Define a helper function js_to_image that takes a JavaScript object containing an image from a webcam and converts it into an OpenCV BGR image.
11. Define a helper function bbox_to_bytes that takes a NumPy array containing a rectangle to overlay on a video stream and converts it into a base64 byte string.
12. Define a function take_photo that captures an image from the webcam, performs object detection using the darknet_helper function, overlays bounding boxes on the detected objects, and displays the result on the screen.

RESULTS AND DISCUSSION

The experimental setup that was used for conducting the experiments consisted of a system running Ubuntu 16.04 Operating System with an Intel core i5 Processor, 16 GB RAM and an Nvidia GTX 1060, 6GB VRAM, CUDA-supported GPU. The codes were implemented in Visual Studio Code and Google Colab.

Obstacle Detection:



When the robot's water sensor or a soil moisture sensor detects the presence of moisture in the soil and water , the sensor emits a red buzzer light that blinks to let the robot know.
Similarly Objects are detected using the ultrasonic sensor. The HC-SR04 sensor employs sound waves to measure the separation between an object in front of it and the sensor. The sensor sends out an ultrasonic pulse, and then it waits to hear if the object returns an echo. The sensor may calculate the object's distance by counting the amount of time it takes for the echo to return.
The user device receives telemetry from the Arduino through a cable, which includes information such as the depth of the water level as measured by the water sensor. Using an ultrasonic sensor, determine how far away the object is from the robot and the presence of soil.

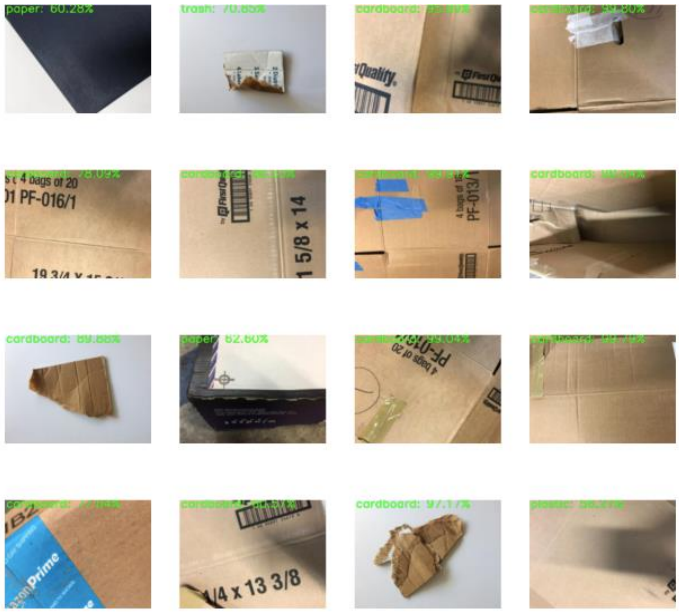
When an obstruction or highly damp soil is present, the robot is prompted to move away from it.

Litter Detection:
Image recognition models are based on pre-trained models (DenseNet121 and MobileNet, trained on ImageNet) provided by Torch and Keras. We fine-tuned MobileNet to classify garbage material based on the TrashNet data collection.
Total Training: 1766
Total Validation: 378
Total test: 383

Classification Report for different Garbage: From this we get 89% Accuracy.

```
[INFO] evaluating after fine-tuning network head...
              precision    recall  f1-score   support

   cardboard       1.00      0.87      0.93        61
       glass       0.85      0.91      0.88        76
       metal       0.88      0.92      0.90        62
       paper       0.91      0.91      0.91        90
     plastic       0.93      0.86      0.89        73
       trash       0.65      0.81      0.72        21

    accuracy                           0.89       383
   macro avg       0.87      0.88      0.87       383
weighted avg       0.90      0.89      0.89       383
```

GARBAGE DETECTION OUTPUT:



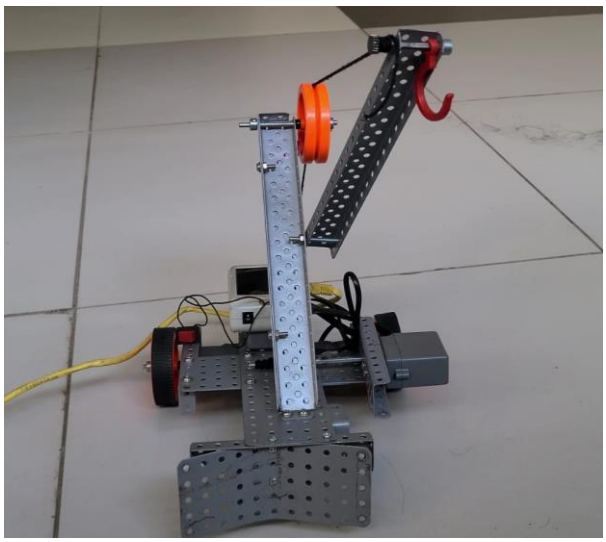
When the litter detection model spots rubbish, the robot's arm slips down and the crane's hook grabs the trash and retrieves it. The robot drops it off after making a short stroll to the garbage can.

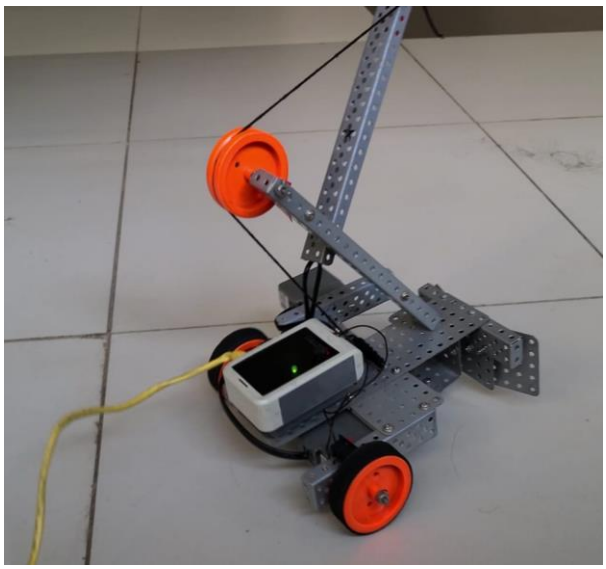
FINAL RESULT:

- The ultrasonic sensors continuously keep calculating the distance between the robot and the object.
- The Soil Moisture sensor checks the presence of damp soil.
- This information gets processed by the ARDUINO.
- If the distance between the robot and the obstacle is less than the specified value, the robot changes its path(moves towards the back). Here, we have kept the minimum distance to be of 15cm.
- The robot walks aside and modifies its course if the ground is too wet and slick for it to move on.
- This process continues forever and the robot keeps moving without danger.
- The arm of the robot moves down and the crane's hook grabs hold of the trash to collect it when the litter detection model identifies the presence of rubbish. The robot then strolls up to the garbage can and places it there.

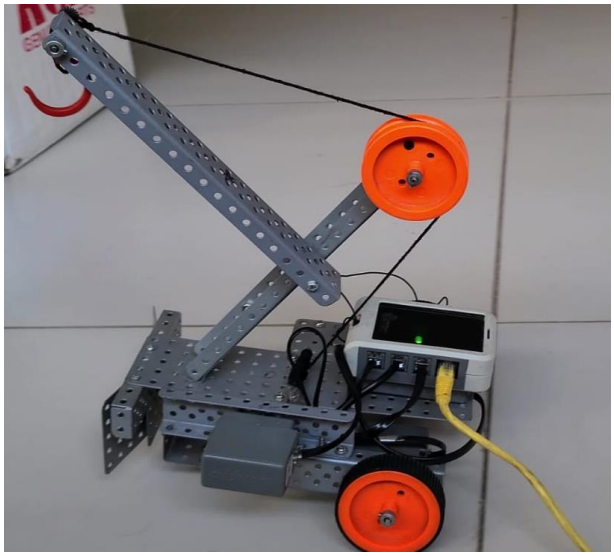
ROBOT MOVEMENT:

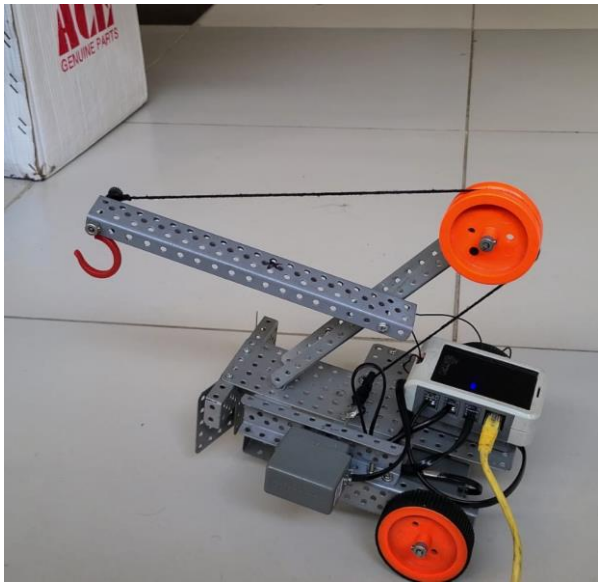
➔ Forward and Backward movement of the Robot:





➔ Up and Down motion of the Robot Crane/Arm.





CONCLUSION:

We are developing a robot with various sensors and actuators that can perform tasks such as detecting moisture in soil and water, detecting objects using an ultrasonic sensor, and detecting litter and retrieving it with a crane arm. The robot is also programmed to move away from obstructions or highly damp soil. This project aims to create a robot that can perform useful tasks autonomously based on the data it collects from its sensors. This has potential applications in various fields, such as agriculture and waste management.

To avoid obstacles , The robot utilizes DC motors and an ultrasonic sensor HC-SR04 can navigate through environments with obstacles with ease. The DC motor's speed and direction control features enable the robot to quickly adapt to changes in its environment, while the HC-SR04 sensor's distance sensing and wide field of view provide accurate obstacle detection capabilities. The low power consumption of the HC-SR04 sensor also makes it an ideal choice for battery-powered robots. Overall, the combination of DC motors and the HC-SR04 sensor is a cost-effective and efficient solution for building an obstacle avoidance robot. By integrating these components, the robot can navigate through complex environments, avoid collisions, and reach its destination safely.

The use of image recognition models for garbage classification has the potential to be a valuable tool in waste management, as it can help automate the process of identifying and sorting different types of waste. This could contribute to more efficient and effective waste management practices, as well as potentially reducing the amount of waste that ends up in landfills or other disposal sites.

FUTURE SCOPE:

- Scaling up: The current system seems to be designed for use in small-scale outdoor environments. There is potential to scale up the system for use in larger areas, such as public parks or industrial sites. This would require developing more robust sensors, improved image recognition models, and stronger and faster robotic arms.
- Integration with other systems: The current system is controlled by an Arduino, but there is potential to integrate it with other systems, such as a cloud-based control center, to enable remote monitoring and control. This could allow multiple robots to work together and cover larger areas more efficiently.
- Improved garbage classification: The current system uses a fine-tuned MobileNet model for classifying garbage material. There is potential to develop more advanced models that can distinguish between different types of rubbish, such as recyclables, organic waste, and hazardous materials. This could improve the efficiency of the system's garbage collection and disposal.

- Energy efficiency: The current system is likely powered by batteries or another energy source. There is potential to improve the system's energy efficiency by developing more efficient motors and mechanisms, and by implementing energy-saving measures such as turning off sensors when they are not needed.
- Autonomous learning: The system you described appears to be programmed to respond to specific conditions and stimuli. However, there is potential to develop machine learning algorithms that enable the system to learn and adapt to its environment over time. This could enable the system to become more effective and efficient at garbage collection and navigation.

APPENDIX:

LITTER DETECTION CODE:

```
from google.colab import drive
drive.mount('/content/drive')

import tensorflow as tf
tf.__version__
import keras
keras.__version__

import pandas as pd
import numpy as np
import os
import zipfile as zf
import shutil
import re
import seaborn as sns
import random

os.listdir(os.path.join(os.getcwd(),"/content/drive/MyDrive/TrashDataset"))

def split_indices(folder,seed1,seed2):
    n = len(os.listdir(folder))
    full_set = list(range(1,n+1))
    random.seed(seed1)
    train = random.sample(list(range(1,n+1)),int(.7*n))
    remain = list(set(full_set)-set(train))
    random.seed(seed2)
    valid = random.sample(remain,int(.5*len(remain)))
    test = list(set(remain)-set(valid))
    return(train,valid,test)

def get_names(waste_type,indices):
    file_names = [waste_type+str(i)+".jpg" for i in indices]
    return(file_names)
```

```
def move_files(source_files,destination_folder):
    for file in source_files:
        shutil.move(file,destination_folder)

subsets = ['train','valid','test']
waste_types = ['cardboard','glass','metal','paper','plastic','trash']

for subset in subsets:
    for waste_type in waste_types:
        folder = os.path.join('data',subset,waste_type)
        if not os.path.exists(folder):
            os.makedirs(folder)

for waste_type in waste_types:
    source_folder =
os.path.join('/content/drive/MyDrive/TrashDataset',waste_type)
    train_ind, valid_ind, test_ind = split_indices(source_folder,1,1)

    train_names = get_names(waste_type,train_ind)
    train_source_files = [os.path.join(source_folder,name) for name in
train_names]
    train_dest = "data/train/"+waste_type
    move_files(train_source_files,train_dest)

    valid_names = get_names(waste_type,valid_ind)
    valid_source_files = [os.path.join(source_folder,name) for name in
valid_names]
    valid_dest = "data/valid/"+waste_type
    move_files(valid_source_files,valid_dest)

    test_names = get_names(waste_type,test_ind)
    test_source_files = [os.path.join(source_folder,name) for name in
test_names]
    test_dest = "data/test/"+waste_type

    move_files(test_source_files, test_dest)


import pandas as pd
import numpy as np
import os
import keras
import matplotlib.pyplot as plt
from keras.layers import Dense,GlobalAveragePooling2D
from keras.layers import Dropout
from keras.applications import MobileNet
from keras.preprocessing import image
from keras.applications.mobilenet import preprocess_input
from keras.preprocessing.image import ImageDataGenerator
```

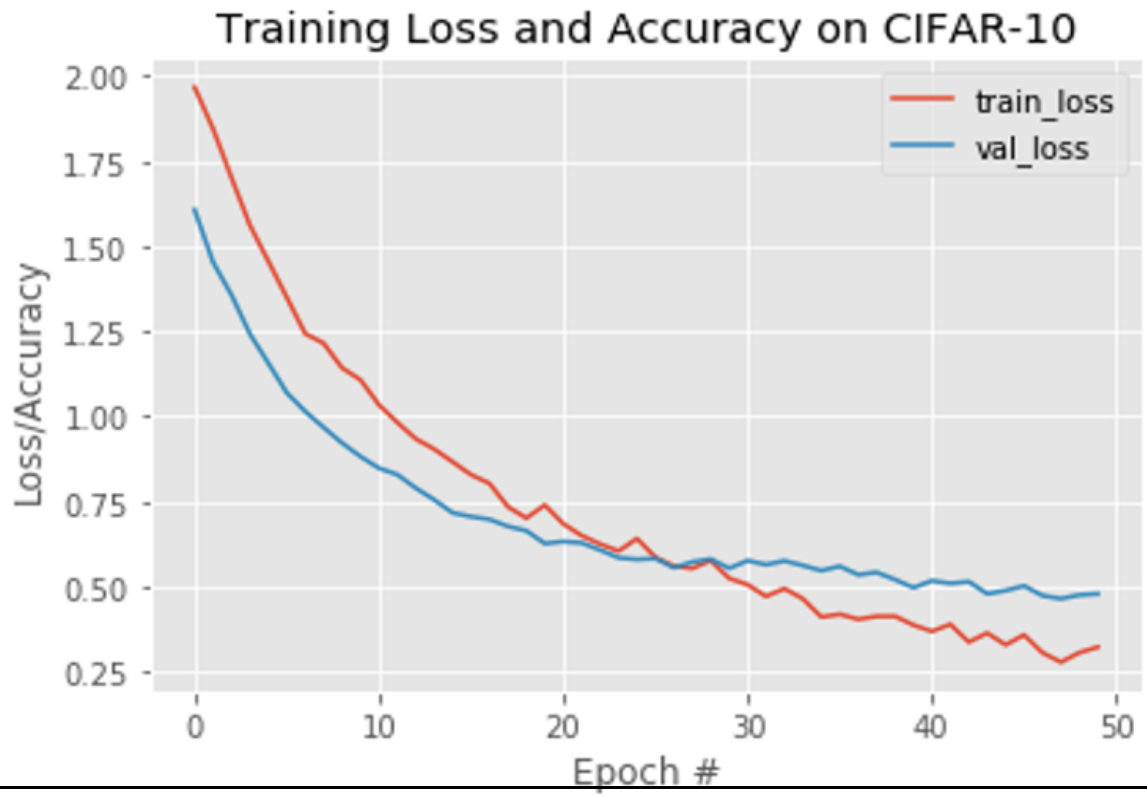
```
from keras.models import Model
from keras.layers import Input
from keras.optimizers import Adam
from sklearn.metrics import  classification_report

base_model=MobileNet(weights='imagenet',include_top=False,
                     input_shape=(224, 224, 3))

base_model.summary()
x=base_model.output
x=GlobalAveragePooling2D()(x)
x=Dense(1024,activation='relu')(x)
x=Dropout(0.5)(x)
x=Dense(1024,activation='relu')(x)
x=Dropout(0.5)(x)
x=Dense(512,activation='relu')(x)
x=Dropout(0.2)(x)
preds=Dense(6,activation='softmax')(x)
model=Model(inputs=base_model.input,outputs=preds)

len(model.layers)

for layer in model.layers[:20]:
    layer.trainable=False
for layer in model.layers[20:]:
    layer.trainable=True

model.summary()

train_datagen = ImageDataGenerator(preprocessing_function=preprocess_input,
                                   fill_mode='nearest',
                                   horizontal_flip=True,
                                   shear_range=0.2,
                                   rotation_range=40,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   zoom_range=0.2)


test_datagen = ImageDataGenerator(preprocessing_function=preprocess_input)

from imutils import paths
train_dir = 'data/train'
validation_dir = 'data/valid/'
test_dir = 'data/test/'
totalTrain = len(list(paths.list_images(train_dir)))
totalVal = len(list(paths.list_images(validation_dir)))
totalTest = len(list(paths.list_images(test_dir)))
print("Total Training: ", totalTrain)
```

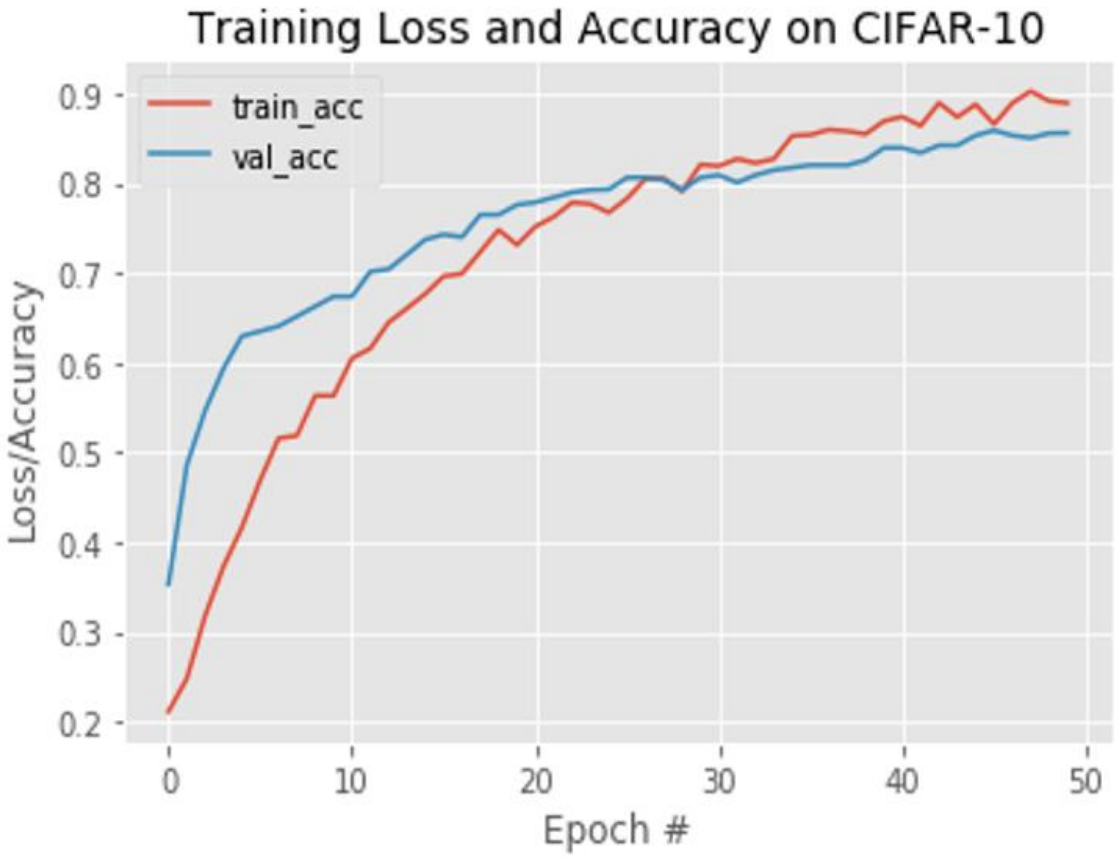
```
print("Total Validation: ",totalVal)
print("Total test: ", totalTest)

BATCH_SIZE = 16
TARGET_SIZE = (224, 224)

train_generator = train_datagen.flow_from_directory(train_dir,
                                                    batch_size=BATCH_SIZE,
                                                    class_mode='categorical',
                                                     color_mode='rgb',
                                                     shuffle=True,
                                                    target_size=TARGET_SIZE)


validation_generator =  test_datagen.flow_from_directory(validation_dir,
                                                    batch_size=BATCH_SIZE,
                                                    color_mode='rgb',
                                                    class_mode='categorical',
                                                    shuffle=False,
                                                    target_size=TARGET_SIZE)


test_generator = test_datagen.flow_from_directory(
    test_dir,
    class_mode="categorical",
    color_mode='rgb',
    target_size=TARGET_SIZE,
    shuffle=False,
    batch_size=BATCH_SIZE)


print("[INFO] compiling model...")
opt = Adam(lr=1e-5)
model.compile(loss='categorical_crossentropy', optimizer=opt,
              metrics=['accuracy'])

print("[INFO] trainning head...")
H = model.fit_generator(
    train_generator,
    steps_per_epoch=totalTrain // BATCH_SIZE,
    validation_data=validation_generator,
    validation_steps=totalVal // BATCH_SIZE,
    epochs=50)

import matplotlib.pyplot as plt

N = np.arange(0, 50)
plt.style.use("ggplot")
plt.figure()
```

```
plt.plot(N, H.history["loss"], label="train_loss")
plt.plot(N, H.history["val_loss"], label="val_loss")
plt.title("Training Loss and Accuracy on CIFAR-10")
plt.xlabel("Epoch
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.figure()
plt.plot(N, H.history["acc"], label="train_acc")
plt.plot(N, H.history["val_acc"], label="val_acc")
plt.title("Training Loss and Accuracy on CIFAR-10")
plt.xlabel("Epoch
plt.ylabel("Loss/Accuracy")
plt.legend()

print("[INFO] evaluating after fine-tuning network head...")
test_generator.reset()
predIdxs = model.predict_generator(test_generator,
     steps=(totalTest // BATCH_SIZE) + 1)
predIdxs = np.argmax(predIdxs, axis=1)
print(classification_report(test_generator.classes, predIdxs,
     target_names=test_generator.class_indices.keys()))

print("[INFO] serializing network...")
model.save('hack_mobilenet.h5')

from keras.models import load_model
import numpy as np
import argparse
import imutils
import cv2
import matplotlib.pyplot as plt
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import load_img
%matplotlib inline
print("[INFO] loading model...")
model = load_model('hack_mobilenet.h5')
from keras.applications.mobilenet import decode_predictions, preprocess_input
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import load_img
import imutils
import cv2
%matplotlib inline
nrows = 8
ncols = 4
pic_index = 0
fig = plt.gcf()
fig.set_size_inches(ncols * 4, nrows * 4)
waste_types = ['cardboard','glass','metal','paper','plastic','trash']
test_d = 'data/test/' + waste_types[0] + '/'
```

```
test_files = os.listdir(test_d)[0:16]
for i, fn in enumerate(test_files):
    sp = plt.subplot(nrows, ncols, i + 1, facecolor='red')
    sp.axis('Off')

    path = test_d + fn
    image = cv2.imread(path)
    img = load_img(path, target_size=TARGET_SIZE)
    output = image.copy()
    output = imutils.resize(output, width=400)
    img = img_to_array(img)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image, TARGET_SIZE)
    image = image.astype("float32") / 255.
    img = np.expand_dims(img, axis=0)
    img = preprocess_input(img)
    preds = model.predict(img)[0]
    i = np.argmax(preds)
    label = waste_types[i]
    text = "{}: {:.2f}%".format(label, preds[i] * 100)
    cv2.putText(output, text, (3, 20), cv2.FONT_HERSHEY_SIMPLEX, 1.05,
        (0, 255, 0), 2)

    plt.imshow(cv2.cvtColor(output, cv2.COLOR_BGR2RGB), interpolation =
'bicubic')

plt.show()
```

OUTPUT:






```
[INFO] evaluating after fine-tuning network head...
              precision    recall  f1-score   support

   cardboard       1.00      0.87      0.93        61
       glass       0.85      0.91      0.88        76
       metal       0.88      0.92      0.90        62
       paper       0.91      0.91      0.91        90
     plastic       0.93      0.86      0.89        73
       trash       0.65      0.81      0.72        21

    accuracy                           0.89       383
   macro avg       0.87      0.88      0.87       383
weighted avg       0.90      0.89      0.89       383
```

OBJECT DETECTION CODE:

```
# import dependencies
from IPython.display import display, Javascript, Image
from google.colab.output import eval_js
from google.colab.patches import cv2_imshow
from base64 import b64decode, b64encode
import cv2
import numpy as np
import PIL
import io
import html
import time
import matplotlib.pyplot as plt
%matplotlib inline

# clone darknet repo
!git clone https://github.com/AlexeyAB/darknet

# change makefile to have GPU, OPENCV and LIBSO enabled
%cd darknet
!sed -i 's/OPENCV=0/OPENCV=1/' Makefile
!sed -i 's/GPU=0/GPU=1/' Makefile
!sed -i 's/CUDNN=0/CUDNN=1/' Makefile
!sed -i 's/CUDNN_HALF=0/CUDNN_HALF=1/' Makefile
!sed -i 's/LIBSO=0/LIBSO=1/' Makefile

# make darknet (builds darknet so that you can then use the darknet.py file and
have its dependencies)
!make

# get bthe scaled yolov4 weights file that is pre-trained to detect 80 classes
(objects) from shared google drive
!wget --load-cookies /tmp/cookies.txt
"https://docs.google.com/uc?export=download&confirm=$(wget --quiet --save-
cookies /tmp/cookies.txt --keep-session-cookies --no-check-certificate
'https://docs.google.com/uc?export=download&id=1V3vsIaxAlGWvK4Aar9bAiK5U0QFttKw
q' -O- | sed -rn 's/.*confirm=([0-9A-Za-
z_]+).*/\1\n/p')&id=1V3vsIaxAlGWvK4Aar9bAiK5U0QFttKwq" -O yolov4-csp.weights &&
rm -rf /tmp/cookies.txt

# import darknet functions to perform object detections
from darknet import *
# load in our YOLOv4 architecture network
network, class_names, class_colors = load_network("cfg/yolov4-csp.cfg",
"cfg/coco.data", "yolov4-csp.weights")
width = network_width(network)
height = network_height(network)

# darknet helper function to run detection on image
```

```
def darknet_helper(img, width, height):
  darknet_image = make_image(width, height, 3)
  img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
  img_resized = cv2.resize(img_rgb, (width, height),
                           interpolation=cv2.INTER_LINEAR)

  # get image ratios to convert bounding boxes to proper size
  img_height, img_width, _ = img.shape
  width_ratio = img_width/width
  height_ratio = img_height/height

  # run model on darknet style image to get detections
  copy_image_from_bytes(darknet_image, img_resized.tobytes())
  detections = detect_image(network, class_names, darknet_image)
  free_image(darknet_image)
  return detections, width_ratio, height_ratio

# run test on person.jpg image that comes with repository
image = cv2.imread("data/person.jpg")
detections, width_ratio, height_ratio = darknet_helper(image, width, height)

for label, confidence, bbox in detections:
  left, top, right, bottom = bbox2points(bbox)
  left, top, right, bottom = int(left * width_ratio), int(top * height_ratio),
int(right * width_ratio), int(bottom * height_ratio)
  cv2.rectangle(image, (left, top), (right, bottom), class_colors[label], 2)
  cv2.putText(image, "{} [{:.2f}]".format(label, float(confidence)),
                    (left, top - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5,
                    class_colors[label], 2)
cv2_imshow(image)

# function to convert the JavaScript object into an OpenCV image
def js_to_image(js_reply):
  """
  Params:
          js_reply: JavaScript object containing image from webcam
  Returns:
          img: OpenCV BGR image
  """
  # decode base64 image
  image_bytes = b64decode(js_reply.split(',')[1])
  # convert bytes to numpy array
  jpg_as_np = np.frombuffer(image_bytes, dtype=np.uint8)
  # decode numpy array into OpenCV BGR image
  img = cv2.imdecode(jpg_as_np, flags=1)

  return img
```

```
# function to convert OpenCV Rectangle bounding box image into base64 byte
string to be overlayed on video stream
def bbox_to_bytes(bbox_array):
  """
  Params:
          bbox_array: Numpy array (pixels) containing rectangle to overlay on
video stream.
  Returns:
        bytes: Base64 image byte string
  """
  # convert array into PIL image
  bbox_PIL = PIL.Image.fromarray(bbox_array, 'RGBA')
  iobuf = io.BytesIO()
  # format bbox into png for return
  bbox_PIL.save(iobuf, format='png')
  # format return string
  bbox_bytes =
'{}'.format((str(b64encode(iobuf.getvalue()), 'utf-8')))

  return bbox_bytes

def take_photo(filename='photo.jpg', quality=0.8):
  js = Javascript('''
    async function takePhoto(quality) {
      const div = document.createElement('div');
      const capture = document.createElement('button');
      capture.textContent = 'Capture';
      div.appendChild(capture);

      const video = document.createElement('video');
      video.style.display = 'block';
      const stream = await navigator.mediaDevices.getUserMedia({video: true});

      document.body.appendChild(div);
      div.appendChild(video);
      video.srcObject = stream;
      await video.play();

      // Resize the output to fit the video element.

google.colab.output.setIframeHeight(document.documentElement.scrollHeight,
true);

      // Wait for Capture to be clicked.
      await new Promise((resolve) => capture.onclick = resolve);

      const canvas = document.createElement('canvas');
      canvas.width = video.videoWidth;
      canvas.height = video.videoHeight;
```

```
      canvas.getContext('2d').drawImage(video, 0, 0);
      stream.getVideoTracks()[0].stop();
      div.remove();
      return canvas.toDataURL('image/jpeg', quality);
    }
    ''')
  display(js)

  # get photo data
  data = eval_js('takePhoto({})'.format(quality))
  # get OpenCV format image
  img = js_to_image(data)

  # call our darknet helper on webcam image
  detections, width_ratio, height_ratio = darknet_helper(img, width, height)

  # loop through detections and draw them on webcam image
  for label, confidence, bbox in detections:
    left, top, right, bottom = bbox2points(bbox)
    left, top, right, bottom = int(left * width_ratio), int(top *
height_ratio), int(right * width_ratio), int(bottom * height_ratio)
    cv2.rectangle(img, (left, top), (right, bottom), class_colors[label], 2)
    cv2.putText(img, "{} [{:.2f}]".format(label, float(confidence)),
                      (left, top - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5,
                      class_colors[label], 2)
  # save image
  cv2.imwrite(filename, img)

  return filename

try:
  filename = take_photo('photo.jpg')
  print('Saved to {}'.format(filename))

  # Show the image which was just taken.
  display(Image(filename))
except Exception as err:
  # Errors will be thrown if the user does not have a webcam or if they do not
  # grant the page permission to access it.
  print(str(err))\

# JavaScript to properly create our live video stream using our webcam as input
def video_stream():
  js = Javascript('''
    var video;
    var div = null;
    var stream;
    var captureCanvas;
    var imgElement;
```

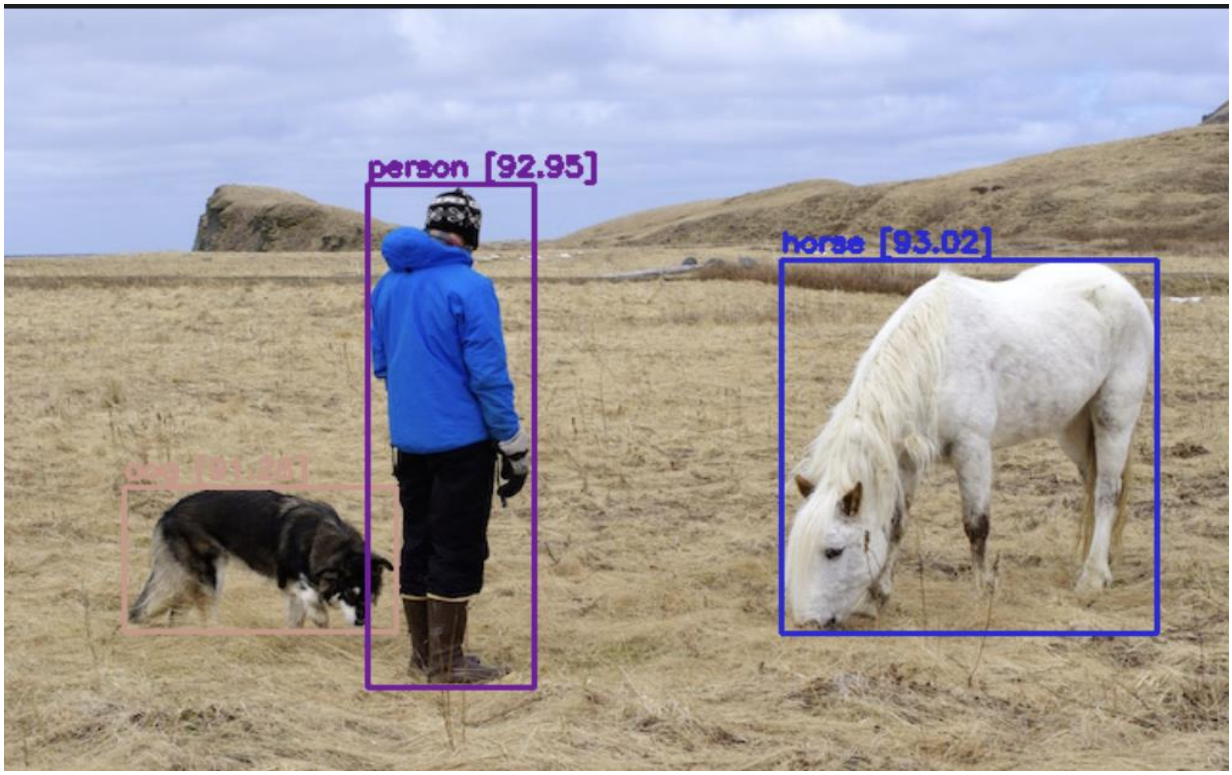
```
var labelElement;

var pendingResolve = null;
var shutdown = false;

function removeDom() {
   stream.getVideoTracks()[0].stop();
   video.remove();
   div.remove();
   video = null;
   div = null;
   stream = null;
   imgElement = null;
   captureCanvas = null;
   labelElement = null;
}

function onAnimationFrame() {
  if (!shutdown) {
    window.requestAnimationFrame(onAnimationFrame);
  }
  if (pendingResolve) {
    var result = "";
    if (!shutdown) {
      captureCanvas.getContext('2d').drawImage(video, 0, 0, 640, 480);
      result = captureCanvas.toDataURL('image/jpeg', 0.8)
    }
    var lp = pendingResolve;
    pendingResolve = null;
    lp(result);
  }
}

async function createDom() {
  if (div !== null) {
    return stream;
  }

  div = document.createElement('div');
  div.style.border = '2px solid black';
  div.style.padding = '3px';
  div.style.width = '100%';
  div.style.maxWidth = '600px';
  document.body.appendChild(div);

  const modelOut = document.createElement('div');
  modelOut.innerHTML = "<span>Status:</span>";
  labelElement = document.createElement('span');
  labelElement.innerText = 'No data';
```

```
  labelElement.style.fontWeight = 'bold';
  modelOut.appendChild(labelElement);
  div.appendChild(modelOut);

  video = document.createElement('video');
  video.style.display = 'block';
  video.width = div.clientWidth - 6;
  video.setAttribute('playsinline', '');
  video.onclick = () => { shutdown = true; };
  stream = await navigator.mediaDevices.getUserMedia(
      {video: { facingMode: "environment"}});
  div.appendChild(video);

  imgElement = document.createElement('img');
  imgElement.style.position = 'absolute';
  imgElement.style.zIndex = 1;
  imgElement.onclick = () => { shutdown = true; };
  div.appendChild(imgElement);

  const instruction = document.createElement('div');
  instruction.innerHTML =
      '<span style="color: red; font-weight: bold;">' +
      'When finished, click here or on the video to stop this demo</span>';
  div.appendChild(instruction);
  instruction.onclick = () => { shutdown = true; };

  video.srcObject = stream;
  await video.play();

  captureCanvas = document.createElement('canvas');
  captureCanvas.width = 640; //video.videoWidth;
  captureCanvas.height = 480; //video.videoHeight;
  window.requestAnimationFrame(onAnimationFrame);

  return stream;
}
async function stream_frame(label, imgData) {
  if (shutdown) {
    removeDom();
    shutdown = false;
    return '';
  }

  var preCreate = Date.now();
  stream = await createDom();

  var preShow = Date.now();
  if (label != "") {
    labelElement.innerHTML = label;
```

```
      }

      if (imgData != "") {
        var videoRect = video.getClientRects()[0];
        imgElement.style.top = videoRect.top + "px";
        imgElement.style.left = videoRect.left + "px";
        imgElement.style.width = videoRect.width + "px";
        imgElement.style.height = videoRect.height + "px";
        imgElement.src = imgData;
      }

      var preCapture = Date.now();
      var result = await new Promise(function(resolve, reject) {
        pendingResolve = resolve;
      });
      shutdown = false;

      return {'create': preShow - preCreate,
              'show': preCapture - preShow,
              'capture': Date.now() - preCapture,
              'img': result};
    }
    ''')

  display(js)

def video_frame(label, bbox):
  data = eval_js('stream_frame("{}", "{}")'.format(label, bbox))
  return data

# start streaming video from webcam
video_stream()
# label for video
label_html = 'Capturing...'
# initialze bounding box to empty
bbox = ''
count = 0
while True:
    js_reply = video_frame(label_html, bbox)
    if not js_reply:
        break

    # convert JS response to OpenCV Image
    frame = js_to_image(js_reply["img"])

    # create transparent overlay for bounding box
    bbox_array = np.zeros([480,640,4], dtype=np.uint8)

    # call our darknet helper on video frame
```

```
    detections, width_ratio, height_ratio = darknet_helper(frame, width,
height)

    # loop through detections and draw them on transparent overlay image
    for label, confidence, bbox in detections:
      left, top, right, bottom = bbox2points(bbox)
      left, top, right, bottom = int(left * width_ratio), int(top *
height_ratio), int(right * width_ratio), int(bottom * height_ratio)
      bbox_array = cv2.rectangle(bbox_array, (left, top), (right, bottom),
class_colors[label], 2)
      bbox_array = cv2.putText(bbox_array, "{} [{:.2f}]".format(label,
float(confidence)),
                          (left, top - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5,
                          class_colors[label], 2)

    bbox_array[:,:,3] = (bbox_array.max(axis = 2) > 0 ).astype(int) * 255
    # convert overlay of bbox into bytes
    bbox_bytes = bbox_to_bytes(bbox_array)
    # update bbox so next frame gets new overlay
    bbox = bbox_bytes
```

OUTPUT:



ARDUINO CODE:

```
// defines pins numbers
const int trigPin = 9;
const int echoPin = 10;
const int buzzer = 11;
const int ledPin = 13;

// defines variables
long duration;
int distance;
int safetyDistance;

void setup() {
pinMode(trigPin, OUTPUT); // Sets the trigPin as an Output
pinMode(echoPin, INPUT); // Sets the echoPin as an Input
pinMode(buzzer, OUTPUT);
pinMode(ledPin, OUTPUT);
Serial.begin(9600); // Starts the serial communication
}

void loop() {
// Clears the trigPin
digitalWrite(trigPin, LOW);
delayMicroseconds(2);

// Sets the trigPin on HIGH state for 10 micro seconds
digitalWrite(trigPin, HIGH);
delayMicroseconds(10);
digitalWrite(trigPin, LOW);

// Reads the echoPin, returns the sound wave travel time in microseconds
duration = pulseIn(echoPin, HIGH);

// Calculating the distance
distance= duration*0.034/2;

safetyDistance = distance;
if (safetyDistance <= 10){
  digitalWrite(buzzer, HIGH);
  digitalWrite(ledPin, HIGH);
}
else{
  digitalWrite(buzzer, LOW);
  digitalWrite(ledPin, LOW);
}

// Prints the distance on the Serial Monitor
Serial.print("Distance: ");
Serial.println(distance);}
```

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